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MASK MANDATES REDUCE COVID-19 MORTALITY: Analysis of 37 States and the District of Columbia, with a further analysis of the impact of demographic and medical factors on efficacy.

ABSTRACT

As the number of COVID-19 deaths in the US increased, various policies were enacted to slow the spread of the pandemic. While the situation has improved in recent months, determining how best to combat the current pandemic is still essential. Failure to do so invites both further resurgences of the current pandemic, and more pandemics in the years to come. As a result of the widespread failure to contain the spread of COVID-19, enough deaths have occurred that the impact of policy on mortality may be statistically evaluated. This paper uses Optimal Discriminant Analysis (ODA) to evaluate the hypothesized ability of limited mask mandates (MM) to reduce the daily number of COVID-19 deaths in the states analyzed. The mandates were found to reduce mortality in half the states analyzed and did not result in increased mortality in any states. A full range of cofactors were analyzed to determine which, if any, influenced the efficacy of the mandates in the states in which mandates had an effect. Institutional Health Subindex of the Social Capital Index, state health score, population density, portion of the population with nongroup health insurance, state GDP, and the rate of pregnancy related diabetes were all correlated with increased mandate efficacy. In contrast, incarceration rate, overcrowded housing, severely overcrowded housing, portion of the population with military provided insurance, portion of the population uninsured, the portion of the population unable to see a doctor due to cost, and the portion of the population who were American Indian/Native Alaskan were all correlated with reduced mandate efficacy.

KEYWORDS: COVID-19, MORTALITY, MASK MANDATE, SOCIAL CAPITAL, PUBLIC HEALTH POLICY, GOVERNMENT POLICY

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INTRODUCTION

At the time of writing the SARS-CoV-2 virus, the cause of COVID-19, has infected 32,356,034 individuals in the United States (9.7% of the population) and killed 576,238 Americans. While 149,462,265 Americans have been vaccinated, only an estimated 32.8% of the population is fully vaccinated [1]. It is estimated that 69.6% of the US population will need to be immune to achieve herd immunity [2].

While immunity builds in the public, policies that reduce mortality remain essential, as does a deeper understanding of the cofactors that strengthen or weaken the impact of those policies.

Several studies have demonstrated the efficacy of Governmental Mask Mandates promoting the wearing of face masks in public [3], in reducing infections [4, 5, 6, 7, 8, 9, 10, 11, 12, 13,14], and reducing mortality [15, 16], associated with COVID-19.

Several medical comorbidities have been associated with increased COVID-19 mortality including cardiovascular disease, obesity, diabetes, and pulmonary disease [17,18, 19, 20, 21, 22]. Demographic factors such as age, rate of nursing home occupancy, rates of incarceration, access to health care, population density and overcrowded housing have been cited as risk factors with COVID-19 [23,24]. Socioeconomic and clinical cofactors are reported by some to account for racial variations in mortality [25,26, 27] whereas other research supports an impact of race as an independent variable [28]. Finally, Social Capital Index has been shown to impact both the rate of infection and mortality of COVID-19 [29,30,31, 32], and fractious partisanship has been shown to worsen the impact of the pandemic [33]. A total of 62 putative cofactors were analyzed to examine how they impact Mask Mandates' effect on COVID-19 mortality (See **Table 1**).

Because Social Capital appears to mediate mortality effects independent of other cofactors [34, 35], an expanded set of Social Capital factors were included in the present study. The focus on state level outcomes in the United States meant that the Social Capital Index [36] was the metric of choice. These included both state level indexes, county level indexes, and county level population-weighted indexes. Additionally, for the state level Social Capital Index all five subindexes and two independent factors were included in the analysis (for more information, see the end of the Data subsection of the METHODS section).

The current study seeks to examine the impact of state-level Mask Mandates on the mortality of COVID-19 and then examine whether these 62 putative cofactors impacted the efficacy of that policy intervention.

There have been reports of political interference impacting the integrity of governmental scientific data including data on COVID-19 pandemic [37,38]. These reports bring into questions the validity of that data. Because of this concern, in the current study, as in earlier studies [4,15], independently curated publicly available data was used [39].

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DEMOGRAPHIC FACTORS			HEALTH RELATED FACTORS	
Population Factors	**Social Capital Factors**	**Wealth & Housing Factors**	**Health Care Access Factors**	**Medical Comorbidities**
Population total [40]	Social Capital Index (SCI); State-Level [36]	GDP State 2109 $M [41]	Medicaid Expansion Yes/No [42]	State Health Score [43]
Children 0-18 [51]	SCI: Family Unity Subindex [36]	GDP $/capita [47]	Insured by Employer [44]	Obesity [45]
Adults 19-25 [51]	SCI: Family Interaction Subindex [36]	Unemployment Rate % JAN 2020 [46]	Insured by Non-Group (Insured Selected) [44]	All Adults who reported Asthma [47]
Adults 26-34 [51]	SCI: Social Support Subindex [36]	Total Unemployment JAN 2020 [45]	Insured by Medicaid [44]	Men with Asthma [42]
Adults 35-54 [51]	SCI: Community Health Subindex [36]	Shelter Beds 2019 [48]	Insured by Military [44]	Women with Asthma [42]
Adults 55-64 [51]	SCI: Institutional Health Subindex [36]	Homeless 2019 [49]	Uninsured [44]	Adults with COPD/ Emphysema/ Bronchitis [42]
Adult 65+ [51]	SCI: Collective Efficacy [36]	Incarcerated per 100,000 adults [50]	Government Hospital beds/1000 [51]	Diabetes? Yes [42]
Ethnicity: White [51]	SCI: Philanthropic Health [36]	Resident Nursing Home per 100,000 adults [52]	Non-Profit Hospital beds /1000 [46]	Diabetes? Yes Pregnancy-Related [42]
Ethnicity: Black [51]	Social Capital Index; County-Level Method [36]	Density pop/sqmi [53]	For-Profit Hospital beds/1000 [46]	Diabetes? No [42]
Ethnicity: Hispanic [51]	SCI: County Population Weighted Index [36]	% Urban [54]	Total Hospital beds/1000 [46]	Diabetes? No Pre-Diabetes or Borderline Diabetes [42]
Ethnicity: Asian [51]		% Overcrowded Housing [55]	All Adults no doctor because of cost [56]	All Adults with Cardiovascular Disease [42]
Ethnicity: American Indian/Native Alaskan [51]		% Severely Overcrowded Housing [40]	Male no doc cost [53]	Men with Cardiovascular Disease [42]
Ethnicity: Native Hawaiian/Other Pacific Islander [51]			Female no doc cost [53]	Women with Cardiovascular Disease [42]

TABLE 1 Cofactors examined for effect of Mask Mandates impact on COIVD-19 Mortality.

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METHODS

Hypotheses

The daily number of deaths in each state, from 30 days before to 50 days after the Mandate, was sourced from the New York Times COVID-19 Data Repository, due to concerns about the reliability of data collected by the federal government as noted above. The dates of the Mask Mandates' implementation were obtained from the COVID-19 US State Policy (CUSP) Database [57]. Mask Mandates for All Public Facing Employees were used, as in previous reports[4,15].

Mask Mandates are hypothesized to reduce the number of COVID-19 deaths by reducing the number of people infected with the virus. People who die of COVID-19 in the immediate aftermath of a Mask Mandate being enacted would have already been infected with the virus before the Mandate took effect, due to the time-course of the infection and associated symptomology. A Mask Mandate is therefore expected to not immediately exert its maximum impact on the number of COVID-19 deaths: rather, a temporal lag (or "offset") will be needed to assess the ultimate impact of the Mandate.

Analysis was conducted to identify the amount of time (number of days) required to attain full effectiveness in reducing the number of deaths due to COVID-19. Sensitivity analysis assessed the strength and stability of ODA models in training analysis and in leave-one-out (LOO) cross-generalizability analysis, sequentially removing post-Mandate data from 1 to 30 days after the Mandate was issued from the analysis. The date on which the maximum effect, measured by ESS, occurred for any given state was used as the lag period for that state.

After the efficacy of each state's Mask Mandate was determined, the states whose Mandates had a statistically significant effect on deaths from COVID-19 were separated into categories according to the size of said effect. The categories were: relatively weak effect (ESS < 25%), a moderate effect (25% <= ESS < 50%), and a relatively strong effect (50% <= ESS < 75%), a strong effect (75% <= ESS < 90%), and a very strong effect (90% <= ESS).

An ODA was then performed to measure the influence of a variety of potential cofactors, using the ESS group of the states (the class variable), and a wide variety of potential cofactors (the attributes).

Data

The daily number of new COVID-19 cases was obtained separately for each State in the 30 days before the Mandate was implemented, and in the 50 days after the Mandate was implemented. Case reports occurring before the Mandate were dummy-coded as class=0, and case reports occurring after the Mandate were coded as class=1. Data from The New York Times, based on reports from state and local health agencies, were initially downloaded from GitHub on January 8, 2021 (data re-confirmed on April 5, 2021) and cross referenced against the COVID-19 State Policy Database (updated March 3, 2021) for dates that Mandates were issued in each State.

Numerical attributes for the analysis of potential cofactors include Social Capital index (State-Level, Using County-Level Methods, and County-Population-Weighted Index, as well as various

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sub-indexes which are listed and briefly explained at the end of this subsection), pre-pandemic population, pre-pandemic GDP (per capita and total), age distribution (with brackets of 0-18, 18-25, 26-34, 35-54, 55-64, and 65+), pre-pandemic (January 2020) number of unemployed persons and unemployment rate, homelessness, shelter beds, incarceration number and rate, population density (people per square mile in 2015), urban overcrowding (number of houses having >1 person per room), severe urban overcrowding (number of houses having >1.5 people per room), percent population by ethnicity (White, Black, Hispanic, American Indian/Alaska Native, and Native Hawaiian/Other Pacific Islander categories), %population with obesity, health insurance status (divided into categories of Ensured by Employer, Ensured by Non-Group, Ensured by Medicaid, Ensured by Medicare, Ensured by Military, and Uninsured), number of hospital beds per thousand individuals (divided into categories of Government, Non-Profit Hospital, and For-Profit Hospital, as well as total beds per thousand), portion of adults who report not seeing a doctor due to cost (male, female, and all adults), adults who reported asthma (male, female, and all adults), adults told they Have COPD/Emphysema/Chronic Bronchitis, adults who reported having diabetes (with pregnancy related cases being counted separately, as well as those with borderline or pre-diabetes), and adults who reported cardiovascular disease (male, female, and all adults). The only categorical attribute included was if the state had expanded Medicaid (yes/no).

The subfactors of the Social Capital index and related indexes examined were: **Family Unity Subindex** (which includes percent of births in past year to unmarried women, percent of women 35-44 currently married (and not separated), and percent of children living in a single-parent family); **Family Interaction Subindex** (which includes percentage of parents reporting 4-plus hours per weekday of child TV time, percent of parents reporting 4-plus hours of child time on electronic devices, and percent of parents reporting someone read to child every day past week); **Social Support Subindex** (which includes percent saying get needed emotional support only (sometimes, rarely, or never), average number of close friends, percentage of neighbors doing favors for each other once-plus per month, and percent who trust all/most of neighbors); **Community Health Subindex** (which includes percent who volunteered with a group past year, percent who attended public meeting regarding community affairs, percent who attended meeting where political issues discussed, percent who worked with neighbors to improve/fix something, percent who served on a committee or as a group officer, percent who participated in demonstration, membership in an organizations per 1,000 residents, and non-profit organizations (including religious congregations) per 1,000 residents); **Institutional Health Subindex** (which includes, voting rate in the 2012 and 2016 presidential elections, mail-back response rate to 2010 census, percent with great confidence in corporations to do what's right, percent with great confidence in the media, and percent with great confidence in public schools); the independent **Collective Efficacy Subindex** (which includes violent crimes per 100,000); and the independent **Philanthropic Health Subindex** (which includes the percent who made a donation of $25-plus dollars to a group in the past year).

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RESULTS

The analysis to determine the delay between the implementation of the Mandate and its effects revealed that the average delay was 22.8 days, with a standard deviation of 6.9 days. This is consistent with CDC estimates of 19 to 23 days between infection and death, depending on age[56].

Hawaii had so few deaths that no analysis of its Mandate's efficacy could be performed, and as such was not included in subsequent analyses. Of the 36 remaining states analyzed, 19 revealed a statistically significant MM effect, with one having a very strong effect (ESS LOO >= 90%), three having a strong effect (75% <= ESS < 90%), four having a relatively strong effect (50% <= ESS < 75%), eight having a moderate effect (25% <= ESS < 50%), and three having a weak effect (ESS < 25%) (SEE **TABLE 2**).

State	Max ESS LOO	Max ESS LOO lag	Max ESS LOO group	Max ESS LOO P-value	ESS LOO for lag = 20	ESS LOO P-value for lag = 20
MA	92.32%	27	4	1.11E-12	70.00%	3.51E-08
LA	75.56%	14	3	2.98E-10	73.33%	5.69E-09
MI	76.36%	28	3	2.35E-08	73.33%	5.69E-09
MN	86.67%	20	3	1.18E-12	86.67%	1.18E-12
IN	53.81%	29	2	0.000106	46.67%	0.00024
VT	53.10%	21	2	0.000013	50.00%	0.000047
NY	63.33%	27	2	4.59E-07	56.67%	0.000001
WA	67.33%	24	2	5.24E-07	62.64%	0.000001
ME	38.57%	29	1	0.006341	0.00%	0.601727
DE	29.05%	29	1	0.026932	20.00%	0.085111
NV	48.33%	30	1	0.000769	23.33%	0.060227
OR	27.27%	6	1	0.014631	23.33%	0.05512
FL	30.00%	20	1	0.017609	30.00%	0.017609
KY	33.33%	19	1	0.006349	32.76%	0.007997
WV	45.00%	30	1	0.00171	40.00%	0.001665
VA	47.62%	29	1	0.000872	43.33%	0.000715

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AK	17.93%	13	0	0.037109	16.67%	0.07275
CA	22.22%	23	0	0.044729	20.00%	0.062639
TX	23.53%	16	0	0.004102	20.00%	0.01186
MS	23.33%	30	NA	0.065889	20.00%	0.052082
NM	25.00%	30	NA	0.069248	13.33%	0.217408
IL	21.90%	29	NA	0.104501	-26.67%	0.993651
GA	12.12%	28	NA	0.183162	-70.00%	1
OH	15.33%	25	NA	0.192575	-26.67%	0.997615
NE	10.00%	30	NA	0.315334	-73.33%	1
CO	7.50%	10	NA	0.346128	-6.67%	0.809173
AZ	8.33%	30	NA	0.354973	3.33%	0.5
AR	5.22%	4	NA	0.385473	3.33%	0.5
PA	3.33%	26	NA	0.555556	-3.33%	0.881356
DC	0.39%	16	NA	0.721726	0.00%	0.754237
NH	-11.67%	30	NA	0.909677	-16.67%	0.99984
UT	-4.67%	0	NA	0.911865	-10.00%	0.973907
NJ	-6.67%	30	NA	0.941837	-26.67%	0.999601
RI	-23.20%	1	NA	0.999457	-30.00%	0.999475
WY	3.33%	*	NA	*	0.00%	0.754237
MD	3.33%	*	NA	*	3.33%	0.5
HI	NA	NA	NA	NA	NA	NA

TABLE 2 A full half of States (19/37) showed a decrease in COVID-19 mortality with Mask Mandates. No States (0/37) showed an increase in COVID-19 mortality with Mask Mandates. Average Lag of 22.8 days with a standard deviation of 6.19 days was found in the 19 States with decreased mortality.

The analysis of cofactors revealed that several cofactors were linked to an increased effect strength of the Mask Mandates in the 19 States in which Mandates had a statistically significant

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effect. Institutional Health Subindex of the Social Capital Index, State GDP, population density, State Health Score, portion of the population insured by non-group health insurance, and rate of pregnancy-related diabetes were the six factors which statistically significantly increased the efficacy of Mask Mandates (See **TABLE 3**). Conversely several cofactors were linked to a weaker effect strength of Mask Mandates. Factors that decreased the efficacy to the Mask Mandates were Incarceration rate, overcrowded housing (both regular and severe), portion of populations with health insurance from the military, portion of population without health insurance, portion of population who reported not seeing a doctor due to cost (regardless of gender) and, portion of the population who were ethnic American Indian/Native Alaskan were all statistically significantly linked to lower effect strength of Mask Mandates (SEE **TABLE 4**).

Factor INCREASED Efficacy of Mask Mandate	**p-value**	**ESS**
Institutional Health Subindex of SCI	0.00836	59.38%
GDP State 2109 $M	0.04228	50.00%
Density ppl/sqmi	0.0336	52.08%
Health Score	0.02744	53.12%
Ensured by Non-Group	0.02272	52.08%
Diabetes? Yes, Pregnancy-Related	0.04692	42.71%

TABLE 3 A total of six factors increased the efficacy of Mask Mandates.

Factor DECREASED Efficacy of Mask Mandate	**p-value**	**ESS**
Incarcerated/100,000 adults	0.02976	52.08%
% Over-Crowded Housing	0.0308	51.04%
% Severely Over-Crowded Housing	0.02904	51.04%
Insured by Military	0.0038	59.38%
Uninsured	0.02356	52.08%
All Adults no doctor because of cost	0.03368	51.04%
Male no doctor cost	0.03088	51.04%
Female no doctor cost	0.03152	52.08%
Ethnicity: American Indian/Native Alaskan	0.004664	37.50%

TABLE 4 At total of six factors, plus three related cofactors, decreased the efficacy of Mask Mandates.

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DISCUSSION

In over half of the States which implemented a Mask Mandate there was a statistically significant reduction in mortality due to COVID-19 infections. Moreover, in States that had no reduction in deaths, Mask Mandates did not increase COVID-19 mortality. Mask Mandates reduced death from COVID-19 in the majority and did no harm in any of the states studied. This shows mask mandates to be a highly effective governmental policy in the face of the COVID-19 pandemic.

The second result to be noted is the strikingly high degree of consistency between the empirically observed lag time demonstrated in this study and the clinically derived estimate of the average time lag between exposure and death from COVID-19. The independently derived estimate by the Centers for Disease Control and Prevention predicts a 19-to-23 day average duration of viral exposure to death in fatal cases of COVID-19 infection [58]. The empirically determined lag between Mask Mandate and reduced mortality of 22.8 days is in complete agreement with the clinical guidance. The agreement between these lag times, determined by two different methods, nonetheless arriving at the same findings, bolsters the validity of the presented analysis.

Several factors had a statistically significant impact on the efficacy of mask mandates. The efficacy of mask mandates in reducing COVID-19 deaths was strengthened by a higher Social Capital Index's Institutional Health Subindex, greater State GDP, greater Population Density, higher State Health Score, higher percentage with Non-Group Insurance, and higher rates of diagnosis of Gestational Diabetes. The Institutional Health Social Capital Subindex had the biggest positive impact on reduction in deaths. This important finding will be discussed further below.

As a generalization it appears as if greater wealth, health, and access to healthcare of choice improves the impact of Mask Mandates. At first glance the helpful influence of percent diagnosed with gestational diabetes seems paradoxical because diabetes is generally considered a risk factor for mortality with COVID-19. However, this finding may be an indicator of more proactive healthcare rather than of true increased rates of diabetes. Rates for gestational diabetes diagnoses vary by the screening method employed. Universal screening (which suggest a more proactive health system) compared with risk factor-based screening leads to more women being diagnosed with gestational diabetes [59]. Rates of gestational diabetes may therefore be a proxy for broader health screening. Broader health screening reflects greater access to health care, which has been shown to improve MM efficacy. This inference is speculative but explains this otherwise paradoxical effect [60].

The factors which reduced the impact of mask mandates include dense living conditions (in jails or in overcrowded housing), military insurance, lack of insurance or lack of a doctor because of cost, as well as Native American/Native Alaskan ethnicity. Native Americans have the highest rate of poverty among any ethnic group [61]. The link between poverty and worse health outcomes is well known [62]. The presence of military insurance among factors decreasing the effect of mask mandates in reducing COVID-19 mortality could be a function of close living (like overcrowded housing), poverty, quality of health care, a military culture of denied vulnerability or some other factor.

Social capital improves the impact mask mandates. It is particularly interesting that specifically the Institutional Health Subindex is the dimension of social capital that impacts mask mandate

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effectiveness. One useful way of understanding of social capital is that it consists of three factors: bonding (relationships with friends and family), bridging (relationship between friends or families) and linking (relationship with a government official or agency) [63]. Typically it is the more individual/ bonding factors of social capital like Family Unity and Family Interaction that impact health outcomes. The more societal/neighborhood aspects of social capital like Community Health and Institutional Health Subindexes are not particularly powerful in determining individual health [64]. And yet, in our analysis, Institutional Health was a powerful factor in increasing the Mask Mandates' efficacy in preventing deaths from COVID-19.

Institutional Health Subindex is one component of the Social Capital Index which is an indicator of confidence in institutions to do what is "right". It is made up of a weighted average of votes in the presidential election per citizen (over 2012 and 2016), the Mail-back response rates for 2010 census and the "Confidence in Institutions Sub-Index" [65], a combination of subjects reporting at least some confidence in corporations, the media, and public schools. It is noteworthy that the impact of social capital Institutional Health index is so strong in this analysis. This finding reveals that trust in institutions which was especially, and perhaps unusually, important for saving lives in the COVID-19 pandemic in the United States.

Moreover, the negative impact of rancorous political debate might be more than merely increasing social discord. If the rancor erodes confidence in institutions, it may pose an actual threat to public health. In the context of the Covid-19 pandemic such political tactics may contribute to the loss of life.

As the process of vaccinating the US population unfolds, trust in public institutions plays an important role. Social Capital, especially general trust, affected vaccinations rates in the 2009 A(H1N1) flu outbreak in the United States [66, 67]. Trust in public institutions (or lack thereof) is highly relevant to the public policies meant to limit the current COVID-19 pandemic as immunization is an essential requirement to get the populace to herd immunity.

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